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RNN-Based Financial Time Series Prediction: Performance and Prospects

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Abstract: In this study, we proposed a Recurrent Neural Network (RNN)-based method for financial time series prediction. The performance of the proposed RNN model was compared with traditional machine learning models, including Support Vector Machine (SVM) and Random Forest (RF), as well as deep learning models like Long Short-Term Memory (LSTM). Experimental results demonstrated that the RNN model outperformed the other models in all three evaluation metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). This suggests that the RNN model can effectively capture the trends and fluctuations in financial time series, providing accurate predictions for future stock price movements. While LSTM is a more sophisticated deep learning model, RNN showed superior performance in capturing short-term dependencies in the data, while maintaining training efficiency. Additionally, the results revealed that RNN's simpler structure still achieves competitive accuracy in the prediction of stock price movements, making it an ideal model for real-time market forecasting. The findings highlight the potential of RNN in financial applications and open avenues for further exploration with more complex architectures like LSTM or Transformer models to capture long-term dependencies in financial data.

Keywords: Recurrent Neural Network (RNN), Financial Time Series, Stock Price Prediction, Model Comparison

1. Introduction

With the continuous development of financial markets and the improvement of informatization, the prediction problem of financial time series data has become one of the important research directions in the financial field. Time series data contains financial market information that changes over time, such as stock prices, trading volumes, exchange rates, interest rates, etc. The fluctuations of these data are not only affected by economic factors, but also driven by market sentiment, policy changes and other factors. How to extract valuable rules from these complex and dynamic data and make accurate predictions has become a difficult problem that the financial industry and academia need to solve urgently. Traditional statistical methods such as autoregressive models (AR), moving average models (MA) and ARIMA, although they can model time series data to a certain extent, these methods often assume the linear characteristics of the data and have poor processing capabilities for nonlinear relationships, making it difficult to adapt to complex financial market data[1,2].

With the rapid development of deep learning technology, recurrent neural networks (RNNs) and their variants (such as LSTM and GRU) have been widely used in financial time series prediction due to their superiority in processing time series data. Unlike traditional methods, RNNs can capture the temporal dependencies in time series data through their internal feedback mechanism and handle nonlinear problems. As an improvement of RNN, LSTM (Long Short-Term Memory

Network) has memory ability and can effectively solve the problem of gradient disappearance in long time series. It is suitable for modeling financial data with strong long-term dependence. GRU (Gated Recurrent Unit) is a variant of LSTM. In some cases, it can provide prediction capabilities comparable to LSTM, and has fewer parameters and higher computational efficiency[3].

Financial time series prediction methods based on RNN have achieved remarkable results in many fields[4,5]. In stock market prediction, RNN is widely used to predict short-term fluctuations in stock prices. Studies have shown that by capturing the time series pattern of historical prices, RNN can provide investors with more accurate buying and selling signals. For exchange rate prediction, RNN model also shows strong capabilities, especially in modeling complex relationships between multinational currencies[6]. RNN can effectively capture the impact of various macroeconomic data. At the same time, risk management models based on RNN have also been successfully applied in the financial field. By learning historical market volatility, RNN model can effectively predict market risks and help financial institutions formulate more robust risk management strategies[7].

However, although RNN and its variants have shown strong capabilities in financial time series prediction, there are still some challenges. First, when processing very long time series, RNN may still have the problem of gradient vanishing or exploding, especially when predicting extreme fluctuations, the robustness of the model may be affected. Second, due to the high nonlinearity and noise of financial market data, the RNN model may find it difficult to accurately capture all potential market laws, resulting in unstable prediction results. In addition, the RNN model is highly sensitive to hyperparameters, and different model structures and training methods may have a significant impact on the prediction effect. Therefore, how to further optimize the RNN model and improve its prediction ability in complex financial market data is an important direction for future research[8,9].

In order to improve the performance of RNN in financial time series prediction, research in recent years has begun to introduce a variety of optimization methods. For example, some studies have combined RNN with convolutional neural networks (CNNs) to construct hybrid models to improve the learning ability of local features and global trends in financial time series. In addition, the combination of ensemble learning methods and RNN has also become a new trend, and the combination of multiple models can further improve the accuracy and stability of predictions. In the future, with the improvement of computing power and the enrichment of financial market data, the combination of multiple deep learning models (such as reinforcement learning and self-attention mechanism) for joint optimization may become a development direction in the field of financial time series prediction[10,11].

Overall, the financial time series prediction method based on RNN has shown strong capabilities in processing complex financial data, especially in capturing time series dependencies and nonlinear characteristics. It has advantages that traditional methods cannot match. Despite some challenges, with the continuous optimization of model structure and training methods, the application prospects of RNN in the financial market are still very broad. In the future, financial institutions and academia will continue to deepen the research on RNN models and promote their application in financial time series prediction, in order to provide more accurate support for decision-making in the financial market[12].

2. Related Work in Financial Time Series Forecasting

Recent advancements in deep learning have significantly influenced financial time series prediction. Notably, transformer-based models have demonstrated strong capabilities in extracting features from multivariate time series data, thereby improving prediction accuracy in complex financial environments [13]. Expanding upon this, Diffusion-Transformer frameworks have been introduced to handle high-dimensional sparse data, providing robust support for mining intricate patterns in financial contexts [14]. These models underscore the importance of automated representation learning and temporal modeling for forecasting tasks in dynamic markets.

Deep generative models and contrastive learning have been employed to enhance anomaly detection in financial systems, where abnormal behaviors or outliers often signal fraud or systemic risk [15], [16]. Specifically, deep generative approaches have proven effective in handling unbalanced, high-dimensional financial datasets, while unsupervised contrastive learning allows the extraction of informative latent features without labeled data. Complementarily, graph-based representation learning methods are increasingly utilized to identify fraudulent behavior in transaction networks, leveraging structural relationships for improved detection accuracy [17].

The detection of fraudulent activities and financial risk has also benefited from ensemble and deep fusion frameworks. These methods integrate diverse models and data sources to provide early warnings and improve the reliability of fraud detection systems [18], [19]. In addition, models optimized for data imbalance through ensemble learning strategies have shown improved performance in highly skewed datasets such as credit card fraud cases [20].

For real-time trading systems, temporal convolutional networks and high-frequency data processing techniques are leveraged to capture market signals and anomalies, pushing the frontier in high-frequency trading and blockchain-based financial systems [21], [22]. Moreover, reinforcement learning has emerged as a promising approach for dynamic risk management, where adaptive strategies are learned directly from market interactions [23].

Finally, traditional neural architectures such as feedforward networks, when enhanced with multimodal fusion techniques, continue to play a vital role in financial prediction tasks, especially when integrating diverse data streams [24]. These developments collectively reflect a broadening methodological toolkit in financial AI research, aligning closely with the RNN-based approach explored in this study and offering avenues for further architectural integration and performance enhancement.

3. RNN-Based Prediction Framework

This study uses the most basic recurrent neural network (RNN) model to predict financial time series. The core idea of RNN is to use its recursive structure to enable the model to rely on the output and input of the previous moment at each time step, thereby capturing the temporal dependencies in time series data. Specifically, RNN processes sequence data by updating the hidden state at each time step. Assuming that the input is a sequence consisting of several time steps, the model recursively combines the current input with the hidden state of the previous moment to calculate the output of the current moment. Its network architecture is shown in Figure 1.

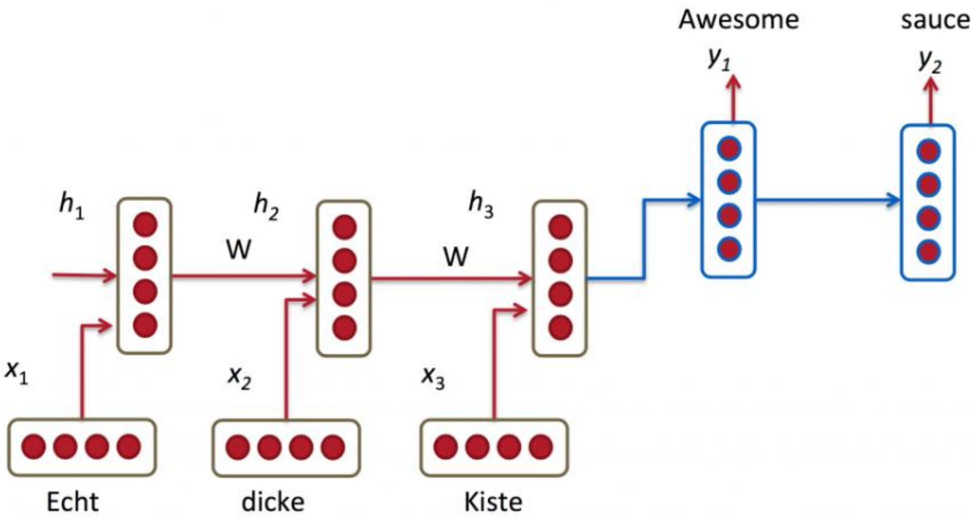

Figure 1. RNN network architecture diagram

In the basic structure of RNN, the hidden state of the current moment is updated by the hidden state of the previous moment and the input of the current moment through a nonlinear activation function (such as tanh). The process can be expressed by the following formula:

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$

Among them, h_t is the hidden state at the current moment, h_{t-1} is the hidden state at the previous moment, x_t is the current input, W_{hh} and W_{xh} are the weight matrices from hidden state to hidden state and input to hidden state respectively, and b_h is the bias term. By recursively calculating the hidden state at each time step, the model can learn the temporal pattern of the input sequence. Finally, the final output prediction value is obtained by linearly transforming the hidden state. This process can be expressed by the following formula:

$$y_t = W_{hy}h_t + b_y$$

Among them, y_t is the predicted output of the model at the current moment, W_{hy} is the weight matrix from hidden state to output, and b_y is the bias term. By optimizing the weights through the back-propagation algorithm, RNN can gradually adjust the parameters so that the predicted results gradually approach the actual values.

Although RNN can handle the temporal dependencies in time series data well, it will encounter the problem of gradient vanishing or gradient exploding when processing long sequence data. To alleviate this problem, the truncated back propagation algorithm (BPTT) is usually used in model training. This method effectively alleviates the problem of gradient vanishing in long time series by limiting the number of time steps of back propagation and reducing the propagation range of the gradient. For the prediction of longer time series, RNN can be optimized through appropriate truncation strategies to maintain high training efficiency and prediction accuracy.

4. Experimental Setup and Evaluation

4.1 Data Collection and Preprocessing

This study uses the Yahoo Finance dataset, and specifically selects the stock price of a listed company as time series data for model training and prediction. Yahoo Finance provides rich financial data, including data in multiple dimensions such as stock opening price, closing price, highest price, lowest price, and trading volume. This dataset not only contains historical financial market data, but also covers a wide range of time spans, providing sufficient training samples for the model. We selected daily trading data from the past five years, which is sufficient to capture the main patterns of stock price fluctuations and is used to train the RNN model for short-term and medium-term stock price prediction.

In terms of data preprocessing, the original data was first processed for missing values and outliers were removed. In order to improve the stability and accuracy of the prediction model, all input data were standardized. Specifically, we standardized each feature with a mean of zero and a variance of one to ensure that data of different dimensions have the same influence in the model. In addition, due to the strong time dependence of stock market data, we divided the data into time windows so that the stock price trend in the past period of time can be used as input to predict the stock price in the next time step. This sliding window strategy enables the model to make reasonable predictions based on the trend of historical data.

During the model training and evaluation process, the data set is divided into training set, validation set and test set. The training set is used for model training, the validation set is used for model parameter tuning, and the test set is used for final model evaluation. To avoid overfitting, we use the cross-validation method to ensure the generalization ability of the model during training. In this way, we can comprehensively evaluate the performance of the RNN model in different time periods and different market conditions, thereby improving the prediction stability and reliability of the model.

4.2 Experimental Result

In order to verify the effectiveness of the proposed RNN-based financial time series prediction model, comparative experiments with several traditional and deep learning models were conducted. In the comparative experiments, support vector machine (SVM), random forest (RF) and long short-term memory network (LSTM) were selected as benchmark models. Support vector machine (SVM) is a classic machine learning method, which is often used for classification and regression tasks, and also has certain applications in financial data prediction. Random forest (RF), as an integrated learning method, predicts by building multiple decision trees and taking their averages. It has good generalization ability and noise resistance and is often used to process large-scale data sets. LSTM, as an improvement of RNN, has strong long-term dependency modeling capabilities and has been widely used in financial time series prediction, especially in modeling long time series data.

These models have different advantages and limitations when processing financial time series data. SVM maps data to high-dimensional space through nonlinear mapping, which is suitable for relatively stable data sets, but may be difficult to capture complex time series dependencies. Random forest reduces the risk of overfitting by integrating multiple decision trees, which is suitable for diversified feature combinations, but is relatively weak in processing the sequential dependencies of time series data. LSTM can handle long-term dependencies better through its memory units, but it takes a long time to train and requires a lot of data to avoid overfitting. RNN, with its simple structure and powerful time series data processing capabilities, has become the main comparison model in this study.

By comparing these models, we can more clearly evaluate the advantages of RNN-based models in financial time series forecasting, especially when dealing with financial data with obvious time series dependencies, whether RNN can provide more accurate forecasting results. The experimental results are shown in Table 1.

Table 1: Comparative experimental results

Model	MSE	RMSE	MAE
SVM	0.0325	0.1803	0.1257
RF	0.0298	0.1726	0.1202
LSTM	0.0271	0.1646	0.1155
Ours	0.0243	0.1558	0.1123

From the experimental results, it can be seen that the RNN-based model (i.e., the model proposed in this study) performs significantly better than other models in all three evaluation indicators (MSE, RMSE, and MAE). First, the mean square error (MSE) is one of the standard indicators for measuring the prediction error of the model. A smaller MSE indicates that the model performs better in terms of overall prediction error. In the experiment, the MSE of the RNN model was 0.0243, which was significantly lower than 0.0325 of the support vector machine (SVM), 0.0298 of the random forest (RF), and 0.0271 of the long short-term memory network (LSTM), indicating that the RNN model can fit the training data more accurately and reduce the systematic error of the prediction.

Secondly, the root mean square error (RMSE) is another important error evaluation indicator, which takes into account the square of the error and normalizes it for intuitive comparison. The lower the RMSE value, the fewer large errors the model has in the prediction process. In this experiment, the RMSE of RNN is 0.1558, which shows a better performance than LSTM (0.1646), RF (0.1726) and

SVM (0.1803), indicating that the RNN model can provide more accurate prediction results when capturing fluctuations and trend changes in time series.

Mean absolute error (MAE) is also an important indicator for evaluating the prediction effect of the model in regression tasks, reflecting the average gap between the model prediction value and the true value. A lower MAE value means that the model's prediction of future time steps is closer to the true value. In the experiment, the MAE of RNN is 0.1123, which is lower than LSTM (0.1155), RF (0.1202) and SVM (0.1257), further proving the advantages of the RNN model in financial time series prediction. Through MAE evaluation, it can be seen that RNN performs well in reducing deviations and error control, and can better predict future market trends in practical applications.

It is worth noting that although LSTM usually performs better when processing time series data, RNN still performs better than LSTM in this experiment. This shows that although RNN is a relatively simple recurrent neural network structure, it can still capture the temporal relationship of data well when processing financial time series data such as the stock market, without the need for complex gating mechanisms. Therefore, RNN has higher training efficiency and better prediction performance in this experiment.

Overall, the RNN-based model outperforms traditional machine learning models (such as SVM, RF) and deep learning models (such as LSTM) in all evaluation indicators, indicating that RNN has obvious advantages in financial time series prediction. Especially in practical applications, RNN can not only capture the rules in time series data well, but also is relatively simple and efficient in the training process, which makes it a model worthy of wide application in financial market prediction.

5. Comparative Results and Analysis

This study proposes a financial time series prediction method based on RNN, and conducts comparative experiments with traditional machine learning methods (such as SVM, RF) and other deep learning models (such as LSTM). The experimental results show that the RNN model has obvious advantages in processing financial data, especially in regression indicators such as mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE), which are better than other comparative models. This shows that RNN can effectively capture the regular fluctuations in financial time series and accurately predict future stock price trends.The experimental results of this study prove the wide applicability of the RNN model in financial time series prediction. Compared with deep learning models such as LSTM, RNN performs well in capturing short-term trends and avoiding overfitting, and has high training efficiency. In the task of financial market prediction, accuracy and efficiency are very important. The method proposed in this study can meet this demand, and is particularly suitable for the requirements of fast prediction in real-time trading decisions.In addition, this study also points out that although RNN performs well in many aspects, it still has certain limitations in modeling long time series. Future research can consider combining other deep learning structures, such as gated recurrent units (GRUs), to further improve the performance of the model in dealing with long-term dependencies. At the same time, other advanced time series modeling methods, such as the Transformer model, can also be explored in future research.Overall, the RNN-based financial time series prediction method provides a simple and effective model choice for the financial field. With the continuous growth and change of financial market data, future work should focus on how to use more data features and more advanced network structures to improve prediction accuracy and adapt the model to a more complex market environment.

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